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Research Article

Drought Assessment Using the Standardized Precipitation Index and Its Association with Climate Anomalies in Kotabumi, West Lampung

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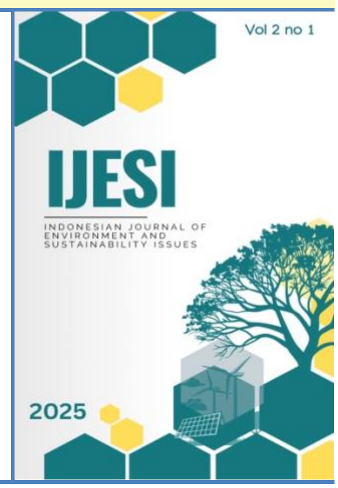
Abstract

This study assesses drought patterns in Kotabumi, West Lampung, Indonesia, using the Standardized Precipitation Index (SPI) at 1-month, 3-month, and 12-month time scales to analyze meteorological, seasonal, and hydrological droughts from 1999 to 2017. The research also explores the relationship between drought severity and global climate anomalies, particularly El Niño and La Niña (ENSO) events. Results show that short-term droughts commonly occur during the dry season (July–October), with several months experiencing extreme drought (SPI < -2.0), such as March 2016 and May 2017. Seasonal droughts, captured through SPI-3, revealed more persistent dry periods primarily in the second half of the year. Long-term analysis suggests that years like 2002, 2006, 2015, and 2016 were marked by sustained rainfall deficits. A clear correlation was found between SPI values and ENSO phases: El Niño years were associated with negative SPI values indicating drought, while La Niña years generally exhibited positive SPI values indicating wetter conditions. These findings demonstrate the effectiveness of SPI in drought monitoring and its utility in developing early warning systems and climate adaptation strategies in drought-prone regions.

Keywords: *Climate Anomalies, Drought, El Niño, ENSO, La Niña*



INTRODUCTION

Drought is a natural hazard characterized by a prolonged deficiency in precipitation that causes water shortages, leading to significant environmental, agricultural, and socio-economic impacts [1]. It is among the most frequent and damaging climate-related disasters, particularly in tropical regions such as Indonesia, where rainfall patterns directly influence agricultural productivity and daily water needs [2]. The effects of drought can be severe, ranging from reduced crop yields and food insecurity to clean water scarcity and economic instability, especially in rural areas heavily dependent on rain-fed agriculture [3]. In West Lampung, particularly in the Kotabumi region, these impacts are intensified due to limited irrigation infrastructure and a strong dependence on seasonal rainfall for farming activities [4]. These vulnerabilities highlight the urgent need for effective drought monitoring and early warning systems to enhance local resilience and adaptive capacity.

To quantitatively assess drought conditions, the Standardized Precipitation Index (SPI) has been widely adopted due to its ability to analyze rainfall anomalies across multiple time scales, such as 1-month, 3-month, and 12-month periods [5],[6]. SPI can represent different types of droughts — meteorological, agricultural, and hydrological—using only precipitation data, which makes it a simple yet powerful tool, particularly in data-scarce environments [7]. Its statistical approach allows early identification of drought onset and intensity, providing valuable information for policy-making and resource planning. The novelty of this study lies in its application of SPI in a specific, rain-dependent agricultural zone in West Lampung that has not been extensively studied in previous drought research. By focusing on this localized context, the research aims to contribute new insights into regional drought dynamics and support the development of adaptive strategies for affected communities.

Numerous studies have demonstrated that SPI fluctuations are significantly influenced by global climate anomalies, particularly the El Niño–Southern Oscillation (ENSO). El Niño generally reduces rainfall in tropical areas, increasing the likelihood of drought, while La Niña tends to bring excessive rainfall and suppress dry conditions [5]. In addition to ENSO, the Indian Ocean Dipole Mode (IODM) also plays a role, particularly in western Indonesia, including Sumatra and Lampung [6]. Drought, a prolonged lack of rainfall, significantly affects agriculture, water supply, and livelihoods, especially in tropical regions like Indonesia. In West Lampung, where rain-fed farming dominates, the risk is critical. The Standardized Precipitation Index (SPI) is widely used to detect rainfall anomalies over multiple timescales, enabling identification of meteorological, agricultural, and hydrological droughts. Its simplicity—relying only on rainfall data—makes it ideal for data-scarce areas. This study applies SPI to assess local drought patterns, offering insights for improved mitigation and adaptation strategies.

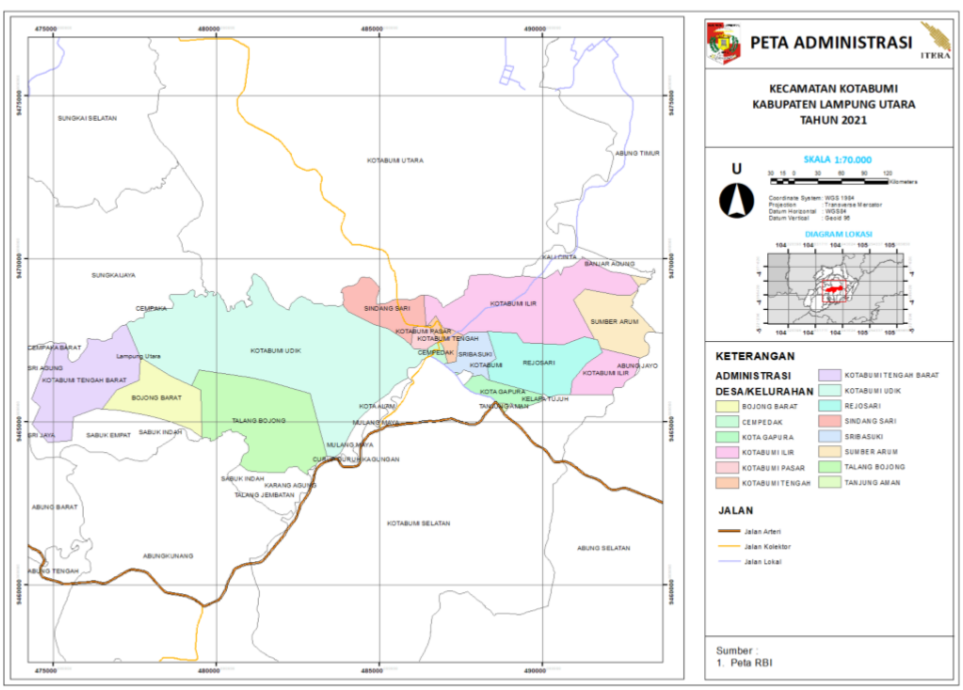
In a recent study, the Lomb Periodogram method was applied to analyze rainfall anomaly frequencies in Lampung Province. The results showed that the Kotabumi region has a dominant anomaly cycle of 4.063 years, aligning closely with El Niño–Southern Oscillation (ENSO) patterns. ENSO, which includes El Niño and La Niña phases, plays a crucial role in modulating rainfall patterns across Indonesia—El Niño typically reduces rainfall and increases drought risk, while La Niña tends to bring above-average precipitation. Additionally, the Indian Ocean Dipole (IOD) also influences regional rainfall variability; a positive IOD can enhance drought severity during El Niño events, while a negative IOD often increases rainfall in western Indonesia. These mid-term climate drivers contribute to rainfall fluctuations that are not merely seasonal but also interannual. However, the use of the Standardized Precipitation Index (SPI) to map seasonal

droughts in direct correlation with ENSO anomalies in Kotabumi remains limited. Therefore, this study aims to analyze seasonal drought characteristics in Kotabumi using the SPI approach and investigate their relationship with global climate anomalies such as ENSO and IOD. The results are expected to support early drought warning systems and guide adaptive strategies for managing water and agricultural resources in the region.

A recent study using the Lomb Periodogram identified a dominant 4.063-year rainfall anomaly cycle in Kotabumi, West Lampung, closely linked to ENSO variability. ENSO significantly influences Indonesia's rainfall—El Niño tends to reduce rainfall, increasing drought risk, while La Niña enhances precipitation. The Indian Ocean Dipole (IOD) further modulates these effects. However, research linking seasonal drought patterns in Kotabumi to these global anomalies remains limited. This study aims to analyze drought characteristics using SPI at 1-, 3-, and 12-month scales, identify extreme drought periods (1999–2017), and examine their relationship with ENSO.

METHODS

This research employs a quantitative descriptive approach with a climatological statistical analysis method. The study focuses on identifying and evaluating seasonal and annual drought patterns in Kotabumi in this **Picture 1**, West Lampung, using the Standardized Precipitation Index (SPI), and assessing its relationship with global climate anomalies, particularly the El Niño–Southern Oscillation (ENSO). The analysis covers the period from 1999 to 2017, and the data are processed using spreadsheet and statistical software through a desk study.



Picture 1. Research Location

The primary data used in this study include monthly rainfall data, obtained from the Meteorology, Climatology, and Geophysical Agency (BMKG) or satellite-based datasets (e.g., GPM, TRMM) if ground station data are unavailable. In addition, ENSO anomaly data, particularly the Niño 3.4

Index or Oceanic Niño Index (ONI), are sourced from NOAA or BMKG archives. This study uses Microsoft Excel to calculate the Standardized Precipitation Index (SPI) at 1-, 3-, and 12-month timescales based on monthly rainfall data from 1999 to 2017 in Kotabumi, West Lampung. The analysis identifies drought periods and examines their link to El Niño–Southern Oscillation (ENSO) and Indian Ocean Dipole (IOD) events. Despite their known impact on rainfall, few studies have used SPI to explore this relationship locally. The findings aim to support early warning systems and climate-adaptive water and agriculture planning. The SPI is calculated for three different time scales: SPI-1 (1-month), SPI-3 (3-month), and SPI-12 (12-month), each representing meteorological, seasonal, and annual drought conditions, respectively. The SPI calculation involves accumulating precipitation values over the defined time scales, fitting the data to a gamma distribution, and transforming the results into a standardized normal distribution (Z-scores). The SPI values are then categorized based on the World Meteorological Organization (WMO) drought classification, ranging from extreme drought (SPI ≤ -2.0) to extremely wet conditions (SPI ≥ 2.0). SPI's strength lies in its ability to evaluate rainfall data across different time scales, useful for monitoring short-term soil moisture and long-term water resources like river flow, groundwater, lakes, and reservoirs. This flexibility makes SPI widely used for drought monitoring and mitigation.

However, SPI has limitations. Values can vary at the same location depending on input parameters such as gamma distribution shape and scale, data period, and probability distribution type (Mishra and Singh, 2010). Also, transformation is necessary because rainfall data typically do not follow a normal distribution throughout the year (McKee, Doesken, and Kleist, 1993). Mathematically, SPI is calculated as the difference between observed rainfall and its mean, divided by the standard deviation for that period:

$$\frac{\boldsymbol{SPI = (Xik - X\bar{\imath})}}{\boldsymbol{\sigma i}}$$

where:
Xik = rainfall in year i, month k
Xi = mean rainfall in year i
σi = standard deviation

According to McKee et al. (1993), SPI values classify drought severity as follows:

Table 1. SPI Category

SPI Value	Drought Category
0 to -0.99	Mild Drought
-1.00 to -1.49	Moderate Drought
-1.50 to -1.99	Severe Drought
≤ -2.00	Extreme Drought

Drought occurs when SPI remains continuously negative (SPI ≤ -1.00), starting when SPI first drops below zero and ending when it returns to positive (McKee et al., 1993). To assess the relationship between SPI and ENSO, the study compares monthly SPI values with the corresponding ENSO indices over the same period. This analysis includes both visual comparisons

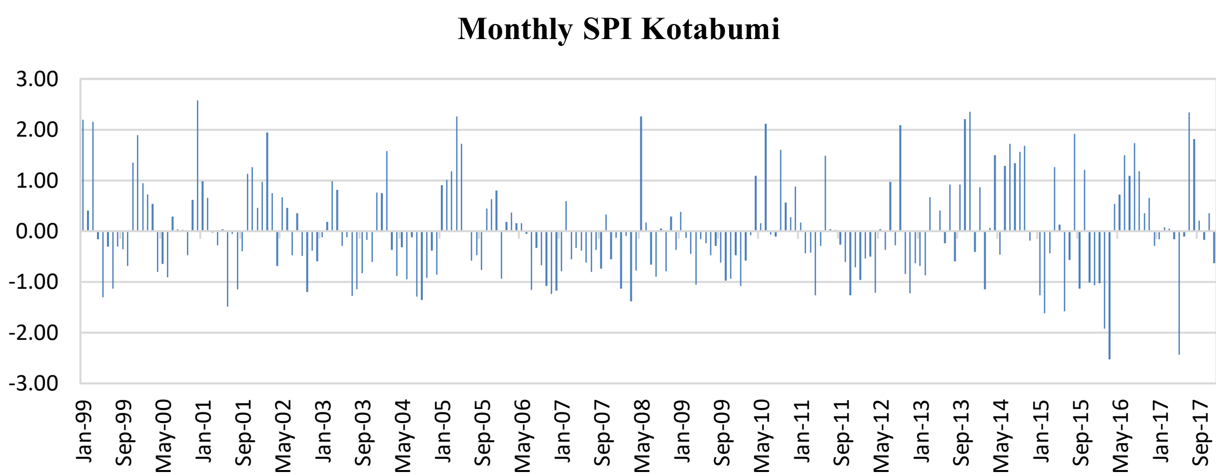
through time-series graphs and descriptive statistical interpretations to identify drought events coinciding with El Niño or La Niña phases.

RESULT AND DISCUSSIONS

This chapter presents the findings of the study, which aimed to assess seasonal and annual drought conditions in Kotabumi, West Lampung, using the Standardized Precipitation Index (SPI) at multiple time scales (1-month, 3-month, and annual), as well as to evaluate the relationship between SPI and global climate anomalies, particularly the El Niño–Southern Oscillation (ENSO).

A. Temporal Variability of Meteorological Drought Based on 1-Month SPI

Meteorological drought refers to short-term rainfall deficits that may occur on a monthly or seasonal basis, affecting surface water availability and initial stages of agricultural stress. The 1-month Standardized Precipitation Index (SPI-1) is widely used to monitor such conditions due to its high sensitivity to fluctuations in monthly precipitation. This time scale is particularly useful for detecting the onset, intensity, and termination of short-term drought events. In this study, SPI-1 values were calculated for Kotabumi, West Lampung, over the period 1999–2017 to observe the variability of meteorological droughts across different years and seasons. The following analysis highlights the temporal distribution of SPI-1 values and identifies the months most frequently associated with drought conditions.



Picture 2. Monthly SPI Index Kotabumi

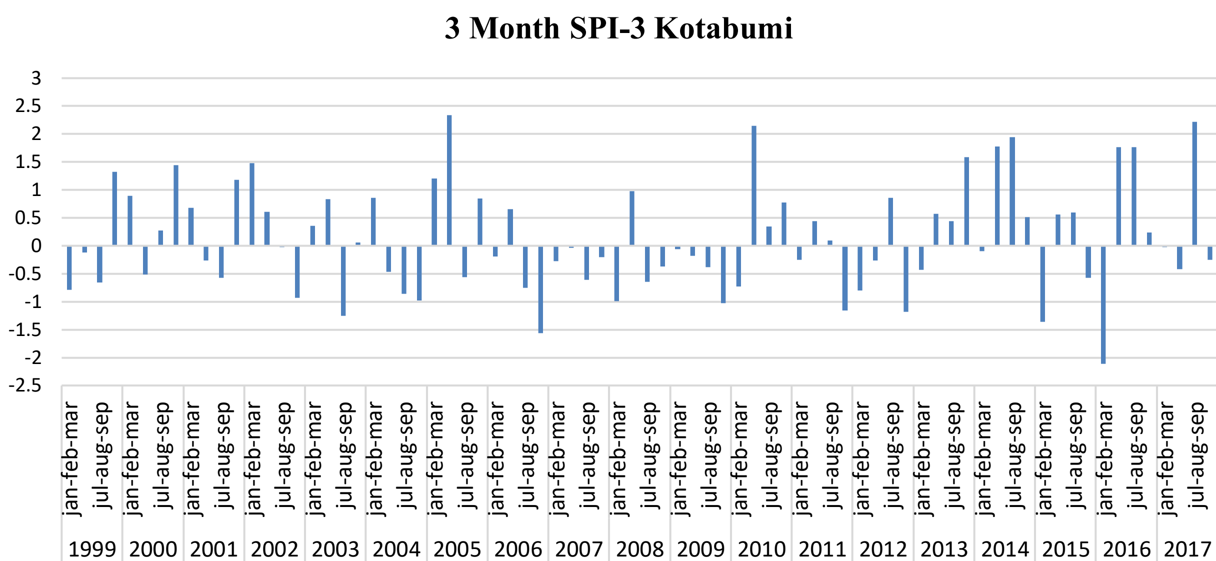
The analysis of 1-month SPI (SPI-1) revealed that meteorological droughts in Kotabumi exhibit high temporal variability and are strongly influenced by monthly rainfall anomalies. Drought episodes were most frequently observed during the dry season months, particularly from July to October, consistent with the regional climatic pattern. Several instances of extreme drought (SPI < -2.0) were identified, notably in March 2016, May 2017, and January 2016, indicating the presence of short but intense rainfall deficits. Due to its sensitivity, SPI-1 proves to be an effective tool for early detection of meteorological drought onset and for monitoring short-term water stress conditions at the local level. Several months recorded extreme drought conditions (SPI < -2), including:

March 2016	:	SPI = -2.59
May 2017	:	SPI = -2.50
January 2016	:	SPI = -1.30

These findings highlight the importance of short-scale SPI monitoring for drought early warning systems and agricultural planning in regions highly dependent on rainfall.

B. Seasonal Drought Dynamics Identified Through 3-Month SPI

Seasonal drought represents prolonged periods of below-average rainfall spanning multiple months, often coinciding with agricultural seasons and water management cycles. The 3-month Standardized Precipitation Index (SPI-3) is designed to capture such patterns by averaging precipitation over rolling three-month intervals, thus smoothing out short-term fluctuations and revealing broader climatic trends. In this study, the SPI-3 was applied to precipitation data from Kotabumi for the period 1999–2017 to evaluate seasonal drought dynamics. This approach allows for the identification of extended dry periods that may not be detected using monthly indices, offering insights into sub-annual drought risks that are critical for agriculture, reservoir operations, and local climate adaptation strategies.



Picture 3. 3 Month SPI Index Kotabumi

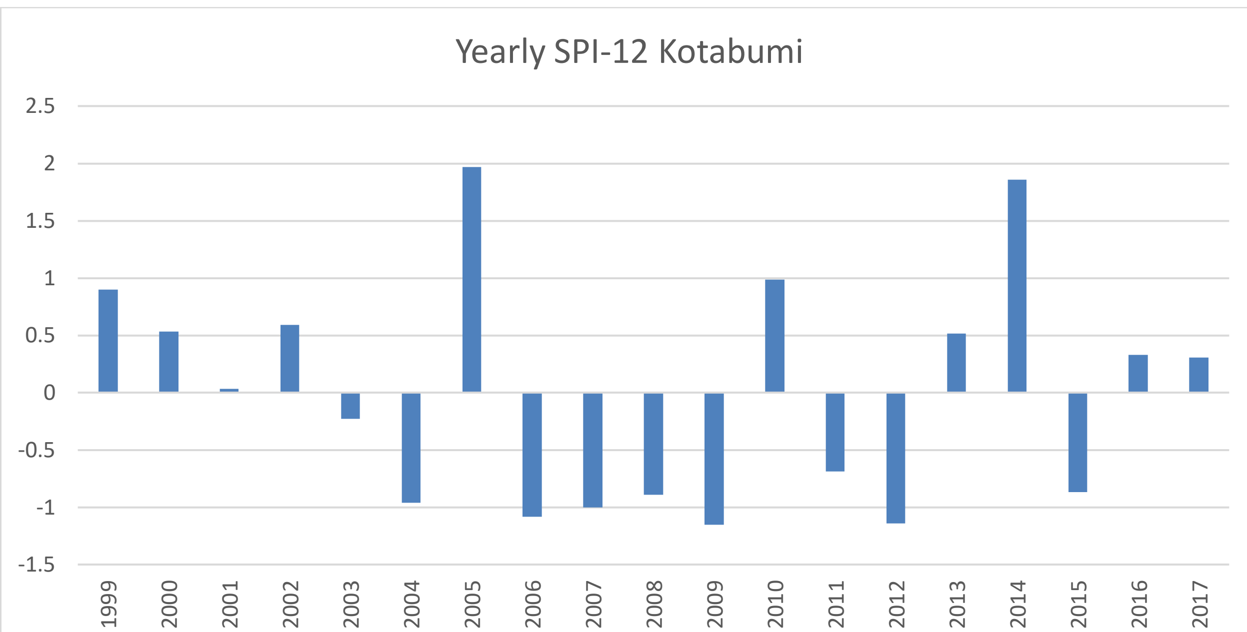
The analysis of 3-month SPI (SPI-3) demonstrates that seasonal droughts in Kotabumi tend to occur consistently during the second half of the year, especially from July to December, aligning with the region's dry season. Compared to SPI-1, SPI-3 provides a more stable representation of precipitation deficits by capturing cumulative effects over multiple months. Several periods of significant seasonal drought were identified, with January 2016 and April 2015 showing extreme negative SPI values. These events reflect not only isolated dry months but also sustained rainfall shortages that can impact agriculture, water supply, and ecosystem health. Notable seasonal droughts include:

January 2016	: SPI-3 = -2.11
April 2015	: SPI-3 = -1.77
July 2017	: SPI-3 = 2.22

These patterns indicate that drought seasons are influenced not only by local dry periods but also by external climate anomalies.

C. Long-Term Drought Trends from Annual SPI Aggregation

Long-term drought, also known as hydrological or groundwater drought, develops over extended periods and can persist even after short-term rainfall returns to normal. This type of drought affects water storage systems, streamflows, groundwater recharge, and agricultural productivity on a broader scale. The 12-month Standardized Precipitation Index (SPI-12) is commonly used to evaluate these long-term conditions by aggregating precipitation data over a full year. In this study, annual drought trends in Kotabumi were examined by observing the cumulative behavior of SPI values throughout each year from 1999 to 2017. While monthly SPI-12 values were not computed explicitly, yearly patterns were inferred from prolonged negative SPI observations, allowing for the identification of drought years characterized by extended precipitation deficits.



Picture 4. Yearly SPI Index Kotabumi

The analysis of long-term drought trends through aggregated SPI values indicates that several years in Kotabumi experienced persistent rainfall deficits, particularly 2002, 2006, 2015, and 2016. These years exhibited predominantly negative SPI values across multiple months, signalling extended periods of drought that likely affected hydrological systems, agricultural output, and water resource availability. Although SPI-12 values were not computed month-by-month, the

inference from SPI-1 and SPI-3 series clearly reflects annual-scale drought patterns. These long-term deficits are especially critical for water supply systems and groundwater-dependent sectors, highlighting the need for continuous monitoring at multi-month to annual scales. Overall, SPI aggregation proves useful for detecting hydrological drought conditions, offering strategic insights for long-term water management and climate resilience planning in drought-prone regions like Kotabumi.

D. Correlation Between SPI Values and ENSO Climate Anomalies

In this study, the ENSO classification is used to compare with SPI values. Typically, El Niño years**,** especially strong ones, are linked to negative SPI values (indicating drought), while **La Niña years** often show positive SPI values (indicating wet conditions). This comparison supports the analysis of how global climate anomalies influence local drought conditions in Kotabumi. The table below shows the classification **of** El Niño and La Niña events from 1951 to 2024 based on their strength: Weak**,** Moderate**,** Strong, and Very Strong. This classification helps identify how different ENSO phases affect rainfall patterns and drought intensity.

Table 2. Classification of El Niño and La Niña Events by Strength and Year (1951–2024)

Category	Strength	Years
El Niño	Weak	1952–53, 1953–54, 1958–59, 1969–70, 1976–77, 1977–78, 1979–80, 2004–05, 2006–07, 2014–15, 2018–19
El Niño	Moderate	1951–52, 1963–64, 1968–69, 1986–87, 1994–95, 2002–03, 2009–10
El Niño	Strong	1957–58, 1965–66, 1972–73, 1987–88, 1991–92, 2023–24
El Niño	Very Strong	1982–83, 1997–98, 2015–16
La Niña	Weak	1954–55, 1964–65, 1971–72, 1974–75, 1983–84, 1984–85, 2000–01, 2005–06, 2008–09, 2016–17, 2017–18, 2022–23
La Niña	Moderate	1955–56, 1970–71, 1995–96, 2020–21, 2021–22, 2007–08
La Niña	Strong	1973–74, 1975–76, 1988–89, 1998–99, 1999–00, 2010–11, 2011–12

The analysis of SPI data across multiple timescales (monthly, seasonal, and annual) demonstrates a clear relationship between drought conditions in Kotabumi and ENSO-related climate anomalies. during El Niño years such as 2002, 2006, 2015, and 2016, SPI values across most months and at multiple timescales were predominantly negative. This indicates significant meteorological and seasonal droughts, particularly during the dry season months (July–October). For example, in 2015, several SPI-1 values fell below -2.0 (extreme drought), and SPI-3 also showed strong drought signals in early and mid-year months. In contrast, La Niña years such as 2010, 2011, 2012, and 2017 were

associated with predominantly positive SPI values, especially during the second half of the year. These values reflect wetter-than-normal conditions, suggesting enhanced rainfall and reduced drought risk during these periods. the annual SPI values further reinforce this correlation. For instance, years with strong El Niño events showed markedly negative annual SPI values (e.g., -1.15 in 2009, -1.14 in 2011), whereas La Niña years like 2010 and 2014 showed positive values (e.g., +0.99 and +1.85 respectively).

Overall, the SPI method effectively captures the impact of ENSO phenomena on rainfall variability and drought intensity in the study area. El Niño events tend to suppress rainfall, resulting in meteorological and seasonal droughts, while La Niña events promote increased precipitation and reduce drought severity. These findings support the use of SPI as a reliable tool for monitoring climate-induced drought risks and for enhancing early warning systems at the local level.

CONCLUSION

This study analyzed drought patterns in Kotabumi, West Lampung, using the Standardized Precipitation Index (SPI) at 1-month, 3-month, and 12-month time scales. It also looked at extreme drought periods between 1999 and 2017 and how droughts relate to El Niño and La Niña (ENSO) events. The SPI-1 results showed that short-term (monthly) droughts often happened during the dry season, especially from July to October. Some months, like March 2016 and May 2017, experienced extreme droughts with SPI values below -2.0. SPI-3 revealed seasonal droughts that lasted longer and were more stable, mostly during the second half of the year. These droughts affected more than just one month and could impact farming and water needs. Annual SPI trends showed that some years, like 2002, 2006, 2015, and 2016, had long-term droughts with mostly negative SPI values, showing a lack of rainfall over the year. Comparing SPI values with ENSO events showed that El Niño years were often linked with negative SPI values (drought), while La Niña years had more positive SPI values (wet conditions). Overall, SPI is a useful tool to monitor droughts and understand how global climate events like ENSO affect local rainfall. It can help in planning for water use and reducing drought impacts in the future.

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AUTHORS CONTIBUTIONS

All authors contributed significantly to the research presented in this manuscript. M.R.I. conceived the study, designed the research framework, and coordinated the collection and preparation of climate data. C.B. contributed to the methodological design, performed the statistical correlation analysis between SPI and ENSO, and assisted in refining the interpretation of results. S.A.M.P.O. carried out the SPI calculations across multiple time scales, analyzed the drought trends, and drafted the initial version of the manuscript. T. supported the preparation of data visualizations, formatted the tables and figures, and contributed to the final manuscript revision. All authors read and approved the final version of the manuscript.

CONFLICT OF INTEREST

The authors declare no conflict of interest. This research, including the selection of the research project, study design, data collection, analysis, interpretation, manuscript writing, and decision to publish, was conducted independently and without any external influence or funding sponsor involvement.

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